

CLASSIFICATION OF ROLLER BEARING FAULTS USING ITERATIVE CLASSIFIER

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ABSTRACT

Bearings play an important role in power transmission systems and to ensure healthy functioning to get the best output. Therefore, a frequent and reliable inspection scheme needs to be employed to intervene before any critical damage occurs. Vibration studies, conducted on bearings reveal useful information, which helps distinguish different working conditions. The data recorded is used to calculate statistical values, which can help diagnose faults in any bearings. This study focuses on classifying the conditions of bearings using statistical features with the help of the Iterative Classifier technique coupled with Multilayer Perceptron in accurately detecting a faulty bearing.

KEYWORDS: Bearings, Fault Diagnostics, Iterative Classifier, MLP & Statistical Features

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INTRODUCTION

Several mechanical machines, mainly rotating ones consist of roller bearings for support. However, bearings are subjected to issues like the lack of lubrication, corrosion, wear and tear, which could lead to sudden failures, which might prove to be expensive, since around 50% of faults in such machines occur due to bearings ((Heng, et al., 2009);(Sawalhi, et al., 2007);(Hoang, et al., 2019)).Of the types of faults that occur in bearings, 90% of them can be attributed to localized faults in the inner and outer races, while the remaining 10% can be attributed to damages in balls and cages(Kateris, et al., 2014). Improper lubrication accounts for roughly 80% of bearing failures (Li, et al., 2009). Moreover, at high temperatures, the lubrication becomes less effective, which causes the lubricant to bleed and make it strong enough to hold the bearing in place, which results in premature failures.

Localized effects mainly due to the removal of sizable material, mostly in contact, resulting due to the continuous operation of machines(Sugumaran, et al., 2008).However, turning off machines for periodic maintenance would not be economical, therefore, the need to know the condition of the bearing, in a non-destructive way would be crucial for any machine to prevent any type of loss due to faulty bearings.

Material properties of the roller bearings and their working parameters, primarily the thermal conditions and the lifetime are crucial in deciding the life of the bearing. The area of contact between the ball and the race is elliptical, which changes when there is a defect and causes vibrations that eventually lead to the bearing's failure (Kong, et al., 2018), which during its lifetime can be countered by resisting the elastic response. However, changes in the microstructure over time can weaken the resistance, by the beginning of micro plastic deformation followed by crack initiation and propagation at micro structural discontinuities, leading to the inevitable failure of the bearing ((Nistane, et al., 2016);(Sadeghi, et al., 2009)).When a localized defect encounters a mating element, there's a sudden change in pressure, causing an impulse, causing a short-lived unexpected vibration (Liu, et al., 2018). The primary source of defects can be attributed to defects caused by foreign particles from impure lubricants

or spall scraps ((Tallian, 2010) a & b). There are two different approaches based on the fault diagnosis of bearings, either to identify the condition of the bearing or to reduce unwanted noise using vibration signal data from the earlier stages of the defect ((Khemili, et al., 2005);(Patel, et al., 2012)). The former is something that is extensively researched and is also discussed in this study.

Several non-destructive techniques, for example, thermal imaging or oil particle analysis have been used to predict the condition of the bearings. The Oil-based analysis is limited to bearing systems which have an oil supply system, while temperature-based analysis can be unreliable towards the end of the bearing's life cycle due to a substantial increase in the system temperature at the end of the cycle, creating false alarms (Heng, et al., 2009). Vibration and sound analysis are commonly used to obtain readings, which can then be used for classification using a suitable machine learning algorithm to correctly predict the condition of the bearing. The position of the sensor should be as close as possible to the bearings to get the best readings and then the data is acquired with the help of a data acquisition system ((Khmelnitsky, et al., 2015);(Akagaki, et al., 2006);(Takabi, et al., 2013)), after which statistical features are calculated from the signals.

Typical vibration signals consist of three unique parts, a stationary vibration, a random vibration and noise. These signals are interpreted with the help of the signal processing techniques like Fast Fourier transform (FFT), wavelets, Hilbert transform etc. The use of these methods helps to clearly understand the signals by applying the appropriate transforms, reducing clutter and displays only the important information from the signals.

Popular methods used for the classification of faults are the Bays classifier, K-star algorithm or the decision tree algorithm. However, these algorithms may not be perfect, for example, the Bays classifier assumes every feature to be independent, while the decision tree method requires a lot of data to train ((Joshuva, et al., 2015);(Sugumaran, et al., 2007);(Amarnath, et al., 2013);(Kumar, et al., 2013);(Sharma, et al., 2017);(Zhang, et al., 2013)).

Artificial Neural Networks (ANNs) are also employed in condition monitoring, which can provide exceptional results even with smaller data sets((Muralidharan, et al., 2010);(Ben Ali, et al., 2015);(Rai, et al., 2016);(Samanta, et al., 2003);(Saxena, et al., 2007)). Multi-layer perceptron (MLP) is an important type of feed-forward based Artificial Neural Network (ANN) and has been used to solve complex problems with proper training algorithms. The input layer consists of a set of input parameters, while the output and hidden layer consist of neurons, based on biological neurons, which contain non-linear activation functions. The weights of the network are initialized to random small values, which are supposed to be updated through multiple iterations. The iterative process employed here is the error back-propagation process, which checks for the error between the desired and the calculated output. The mean square error is calculated as

$$E_{total} = \frac{1}{n} \sum_{i=1}^n E_n \quad (1)$$

Where,

$$E_n = \frac{1}{2} \sum_{k=1}^m \zeta_k^n - O_k^n \quad (2)$$

ζ_k – k^{th} component of the desired output vector.

O_k – k^{th} component of the actual output vector.

The training process stops when the total error becomes less than the minimum error, after which the final weights are stored, and the classification accuracy is calculated. However, using traditional ANN can over-fit the data which

reduces the overall efficiency; therefore, this study is focused on using an iterative classifier which can improve the efficiency of the model and produce more reliable results. A model's efficiency can be evaluated with the help of a confusion matrix, which provides data on a number of correctly and incorrectly classified instances. Quantities such as the precision and recall can be used to provide a deeper understanding of the confusion matrix since precision denotes the availability of related quantities while recall denotes the availability of correct quantities. The overviews of the quantities to be used to understand the confusion matrix are as follows:

$$\text{Precision} = \frac{\text{True positives (TP)}}{\text{True positive (TP) + False positive (FP)}} \quad (3)$$

$$\text{Recall} = \frac{\text{True positives (TP)}}{\text{True positive (TP) + False negative (FN)}} \quad (4)$$

$$MCC(\text{Matthews Correlation Coefficient}) = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (5)$$

$$F1 - \text{measure} = \text{Harmonic mean of recall and precision} = \frac{2TP}{2TP + FP + FN} \quad (6)$$

More than one quantity is used to interpret the confusion matrix since there is no single quantity which can determine the true quality of the model.

EXPERIMENTAL SETUP

Four sets SKF R7 NB 62 bearings were used, with a motor speed of 1200rpm. Defects were created artificially with the help of pits, created by the Electrical Discharge Machining process, on the two major rolling elements of the bearing, the inner and outer races. The pits were close to 0.7mm. A Brüel & Kjær 4096 accelerometer with a conditional amplifier was used to acquire vibration signals and a two-channel FFT analyzer (A&D AD 3525) was used to process these signals. Each bearing was observed separately under the same working conditions with the help of acceleration-time plots.

Four conditions of the bearings were studied:

- Healthy bearings
- Outer race faults
- Inner race faults
- Faults on both rolling elements

For the classification of the signals, 30 signals from each condition were used, resulting in 120 unique signals.

Figure 1 Illustrate the block diagram of the experimental setup.

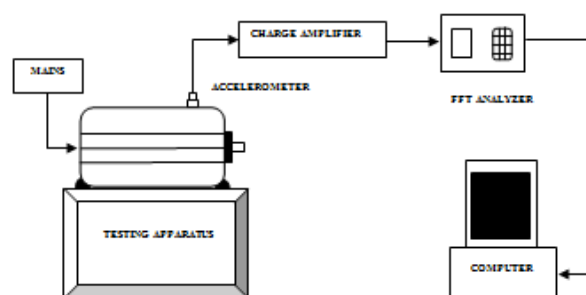


Figure 1: Experimental Setup.

Table 1: Roller Bearing Dimensions

Parameter	Dimensions
Average diameter (mm)	14mm
Ball diameter (mm)	4mm
Number of rolling elements	7
Contact angle	0
Inner ring speed	0 rpm
Outer ring speed	1200 rpm
Healthy condition	33.3 Hz
Frequency of inner race fault	149 Hz
Frequency of outer race fault	84 Hz

The statistical features used for classification were mean, median, mode, standard error, standard deviation, sample variance, skewness, kurtosis, maximum, minimum, sum and range. The information regarding some of these features is follows:

- **Standard Error:** It is a quantity which talks about the amount of error in predicting the dependent value y for an independent value x in the regression.

$$\text{Standard Error of } Y = \sqrt{\frac{1}{n-2} \left[\sum (y - \bar{y})^2 - \frac{[\sum (x - \bar{x})(y - \bar{y})]^2}{(x - \bar{x})^2} \right]}$$

where,

n -sample size

Standard Deviation: This quantity is useful to determine the credibility of the vibration signals since it provides information on how the data deviates from the mean.

$$\text{Standard Deviation} = \sqrt{\frac{\sum x^2 - (\sum x)^2}{n(n-1)}}$$

Sample Variance: It is a quantity which shows the variance amongst signals. It is equal to the squared value of standard deviation.

Kurtosis: This quantity indicates the nature of a signal, a low value (a flat curve) indicates a normal signal, while a high value (sharp curve) indicates a faulty condition.

$$\text{Kurtosis} = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

where

s -standard deviation

Skewness: It denotes the degree of irregularity of a distribution with respect to the mean.

$$\text{Skewness} = \frac{n}{n-1} \sum \left(\frac{x_i - \bar{x}}{s} \right)^3$$

Range: The difference between the maximum and the minimum values of a dataset

Maximum value: The maximum value of a given dataset.

Minimum value: The minimum value of a given dataset.

Sum: The total of all points in a dataset.

The minimum and maximum values of a dataset can be used to determine defects since the vibration levels observed from faulty bearing elements are high (Sugumaran, et al., 2008).

The statistical features were classified using the iterative classifier optimizer method, which optimizes an iterative classifier, in this case, the Multi-Layer Perceptron method, to perform the least number of iterations based on percentage-split evaluation or cross-verification.

The learning rates and the momentum values were altered from 0.1 to 1 each to achieve the highest classification accuracy, using the 10-fold cross-verification method.

RESULTS

As mentioned earlier, the momentum and learning rates of the ANN were varied, to get the highest classification accuracy possible, with a constant number of hidden layers. The best classification accuracy of 81.67% was obtained with the learning rate of 0.3 and a momentum of 0.1 (refer table 2). The lowest classification accuracy was 25% and the average accuracy obtained was 70.5%.

Table 2 depicts the confusion matrix, in which the diagonal elements show the number of correctly classified elements. According to the confusion matrix, a single outer race defect can be accurately classified without any error, which is also denoted by the high recall and precision values, followed by a single inner race defect and two outer race defects.

In table 4, the TP (true positive) rates are close to one while the FP (false positive) rates are almost zero which confirms the credibility of the model. Moreover, the values of precision and recall are also close to one, denoting that the model can successfully identify most of the relevant quantities from a dataset, which is also confirmed with the help of F-measure, which considers both of these quantities to provide a score, an average of 0.81.

The ROC (Receiver Operating Characteristic) area is more than 0.5, meaning that the model is not a failure and is quite useful. The PRC (Precision Recall Curve) area is used as a supplement to the ROC area, which denotes the reliability of the model.

Table 2: Confusion Matrix

	a	b	c	d	Predicted Condition Actual Condition
a	21	3	6	0	a-Healthy
b	4	21	5	0	b-2 outer race defects
c	3	1	26	0	c-Inner race defect
d	0	0	0	30	d-1 outer race defect

Table 3: Classification Accuracy with Changing Momentum and Learning Rates

Learning Rate Momentum	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
0.10	78.83	80.00	78.33	78.33	76.66	80.83	76.66	80.00	78.33	25.00
0.20	78.33	77.00	78.33	79.16	78.33	78.33	79.16	80.83	77.50	30.00
0.30	81.66	79.19	77.50	79.16	78.33	80.83	77.50	76.66	73.33	27.50

Table 3 Contd.,										
0.40	79.16	80.83	80.00	80.00	76.66	78.33	79.16	73.33	75.00	30.00
0.50	78.33	79.16	78.33	75.83	75.83	80.00	73.33	72.50	62.50	32.50
0.60	80.00	78.33	75.83	78.33	75.83	79.16	73.33	75.00	61.66	30.00
0.70	76.66	74.33	75.83	75.83	80.00	80.00	73.33	74.16	51.66	27.50
0.80	75.00	75.83	79.16	78.33	79.16	74.16	75.00	70.83	45.00	32.50
0.90	75.83	76.67	75.00	78.33	80.83	74.16	75.83	70.83	29.16	27.50
1.00	75.00	79.16	76.66	76.66	80.83	76.66	75.00	72.50	25.00	25.00

Table 4: Detailed Accuracy by Class

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.70	0.07	0.75	0.700	0.72	0.63	0.88	0.70	Healthy
	0.70	0.04	0.84	0.700	0.76	0.69	0.85	0.77	2 outer race defects
	0.86	0.12	0.70	0.867	0.77	0.69	0.91	0.72	Inner race defect
	1.00	0.00	1.00	1.000	1.00	1.00	1.00	1.00	1 outer race defect
Weighted Avg.	0.81	0.06	0.82	0.817	0.81	0.75	0.91	0.79	

CONCLUSIONS

Bearings are essential to machine elements in the industry; however, constant use gives way to thermal expansion and interaction with foreign particles, resulting in the inevitable failure of the component due to fatigue. Several conditions monitoring studies use different techniques to correctly identify the condition of a roller bearing. Vibration signals were processed using the FFT method and the statistical features used were mean, median, mode, standard deviation, variance, kurtosis, skewness, minimum, maximum and sum. This study provides a method to enhance the classification efficiency of the ANN model for bearing condition monitoring with the help of an iterative classifier. The optimized ANN model was able to gain a classification accuracy of 81.67% without the aid of a large data set. The credibility of the model is verified with the help of the confusion matrix which has reasonable values of TP rate, FP rate, recall and other important quantities. This setup can detect inner and outer race defects of a bearing, which will enable timed intervention to prevent any damage.

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